# Temporal variations of bicycle demand in the Netherlands: The influence of weather on cycling

Tom Thomas, Rinus Jaarsma and Bas Tutert

**T. Thomas, corresponding author:** Centre of Transport Studies, University of Twente, p.o.box 217, 7500 AE Enschede, the Netherlands, tel: +31 53 4893821, fax: +31 53 4894040, t.thomas@utwente.nl

**C.F. Jaarsma**: Land Use Planning Group**,** Wageningen University, p.o.box 47, 6700 AA Wageningen, the Netherlands, tel: +31 317 48 3552, fax: +31 317 419000, rinus.jaarsma@wur.nl

**S.I.A. Tutert:** Centre of Transport Studies, University of Twente, p.o.box 217, 7500 AE Enschede, the Netherlands, tel +31 53 4894517, fax: +31 53 4894040, s.i.a.tutert@utwente.nl

**Date:** November 7, 2008

**ABSTRACT**
The variability in bicycle demand depends strongly on weather. This paper describes a 'weather' model that makes demand forecasting possible. The model is based on flow time-series of many years, collected at 16 cycle paths in the Dutch cities of Gouda and Ede. The model is bi-level. The lower level describes how cyclists value the weather. The upper level is the relation between demand and this weather value. The observations show that most cyclists value the weather in a similar way, but recreational demand is much more sensitive to weather than utilitarian demand. Most fluctuations are described by the model, but a significant fraction is still not covered. From a correlation analysis of the residuals, we conclude that about 70% of the remaining variation is locally constrained, and can therefore not be described by a generic model. However, about 30% of this variation is not driven by local effects. The cause of this variation is not yet known. Besides uncovering trends in cycling, the model can also be employed to evaluate the effect of cycling policy interventions, and to correct flow measurements as input in traffic models.

## 1. INTRODUCTION

Cycling is an important mode of transport in the Netherlands. It is healthy, sustainable, cheap and it plays a part in reducing congestion. It is therefore not surprising that cycling is supported by the government, and that several measures are taken to increase its demand. It is the task of traffic managers to monitor whether introduced measures have a positive effect.

Several authors used aggregated models to describe trends in bicycle demand using census data. This was done in the US, e.g. (*1*), (*2*), in the UK, e.g. (*3*), (*4*), and in the Netherlands, e.g. (*5*). These studies included physical and social factors. (*4*) showed that hilliness, temperature and rain have a significant influence on demand, and (*5*) found several factors that cause differences in bicycle demand between Dutch municipalities.

Relatively little is known about the relation between weather and bicycle demand. Several studies have however shown that weather has a strong influence on demand, e.g. (*6*), (*7*), (*8*), (*9*). The influence of weather on bicycle demand is a complicating factor. It will for example make little sense to compare demands at different locations when they have been measured during different weather conditions.

Besides census data, demand can be determined by measuring the flows on cycle paths, e.g. (*10*). If the relation between weather and demand is known, weather corrections could be made to 'standardize' these flows. In that case, flows from very specific locations, but also from different years, can be compared. This information can be used in studies that evaluate policy measures for the improvement of cycling circumstances.

In this paper we introduce a model that relates bicycle demand to all weather parameters provided by the Dutch Meteorological Institute. It is an extension of previous work (*10*) and (*11*). In section 2 we describe the data that are used. Section 3 describes the model. In section 4 we show the results, and in section 5 the results are validated. Section 6 ends with conclusions.

## 2. DATA

In the last few decades, the Wageningen University gathered 24 hour cycle flows on cycle paths throughout the Netherlands. These flows were measured by pneumatic tubes. From this large data set we selected data from 16 cycle paths, located in the countryside near the cities of Gouda (in the west of The Netherlands) and Ede (in the center of The Netherlands). The following types of cycle paths were distinguished: utilitarian, mixed and recreational. The allocation was based on knowledge of the local situation and appears to be correct. In Table 1 we give an overview of the data set. In Figure 1 the measuring points are presented geographically. The utilitarian paths are connecting municipalities, whereas recreational paths open up the country side for citizens. Mixed paths combine these functions.

In Figure 2 we show the flow time-series for the recreational path with ID 0725 (left panel) and for the utilitarian path with ID 5501 (right panel). This is done for the whole measurement period (upper panel), and as an example for the year 1993 (bottom panel). Both cycle paths are representative for the sets.

**TABLE 1 The data: location, type of path, and period of data gathering**

| ID | Location | Type | Period |
|---|---|---|---|
| 0740 | Ede | Utilitarian | 1990 – 1994 |
| 0727 | Ede | Mixed | 1993 – 2003 |
| 0738 | Ede | Mixed | 1993 – 2003 |
| 0725 | Ede | Recreational | 1993 – 2003 |
| 0729 | Ede | Recreational | 1993 – 2003 |
| 0731 | Ede | Recreational | 1993 – 2003 |
| 0732 | Ede | Recreational | 1993 – 2003 |
| 0736 | Ede | Recreational | 1993 – 2003 |
| 5504 | Gouda | Utilitarian | 1987 – 1993 |
| 5501 | Gouda | Utilitarian | 1987 – 1993 |
| 5502 | Gouda | Utilitarian | 1987 – 1993 |
| 5503 | Gouda | Utilitarian | 1987 – 1993 |
| 5508 | Gouda | Mixed | 1990 – 1993 |
| 5507 | Gouda | Mixed | 1990 – 1993 |
| 5505 | Gouda | Recreational | 1987 – 1993 |
| 5506 | Gouda | Recreational | 1987 – 1993 |

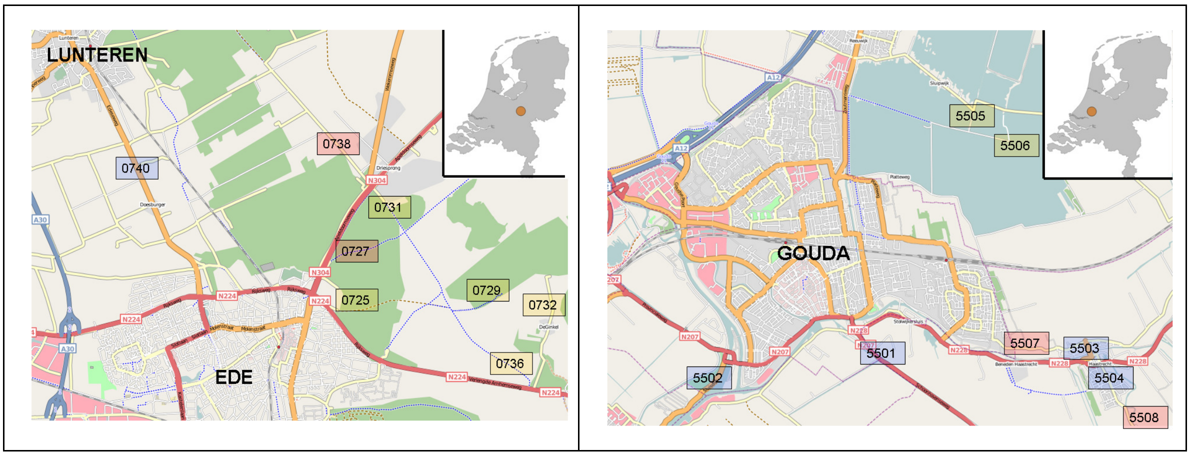


**FIGURE 1 Location of measuring points around the cities of Ede (left panel) and Gouda (right panel). Blue stands for a utilitarian, yellow/green for a recreational and red for a mixed function. OSM; Open Street Map**

Both time-series in Figure 2 show an increase in demand during spring, and a decrease after the maximal demand in (the beginning of) summer. There are however also clear differences between the recreational and utilitarian time-series. The utilitarian path shows a repetition of dips which coincide with the weekends. The recreational path shows strong peaks. Some of these coincide with the Dutch bank holidays. Because of their unique character, bank holidays are left out of the sample. The school holidays show a high demand for the recreational path, and a low demand for the utilitarian path. The school holidays contain the weeks 52-1, 7-10, 18-19, 28-36 and 42-43 in the particular regions.

In order to reject possible false measurements, we used the following method. For each week number (1 – 53), day of the week (Monday till Sunday), and cycle path, we estimated the median 24 hour flow over the years. We assumed that if a measurement lies below 10% of the median, this measurement would probably be false. The most common cause of such a false measurement is a temporally malfunctioning of the road tube. We excluded all such measurements, where the median flow was larger than 10 counts per day (because for small volumes, relatively large variations may occur naturally). By adopting this selection criterion, we excluded less than 1% of all measurements.

The weather 'observables' (e.g. temperature and precipitation) are provided by the Dutch National Meteorological Institute (KNMI), and can be downloaded free of charge from their website (*12*). There are several weather stations, but we used data only from station De Bilt, because it is in the proximity of both Ede and Gouda. Therefore, the weather data do not necessarily present the local weather conditions. Moreover, only 24 hour aggregates are provided, which lead to more uncertainties (e.g. a wet night will have a negative contribution in the demand estimate, even if it is sunny during day-time).

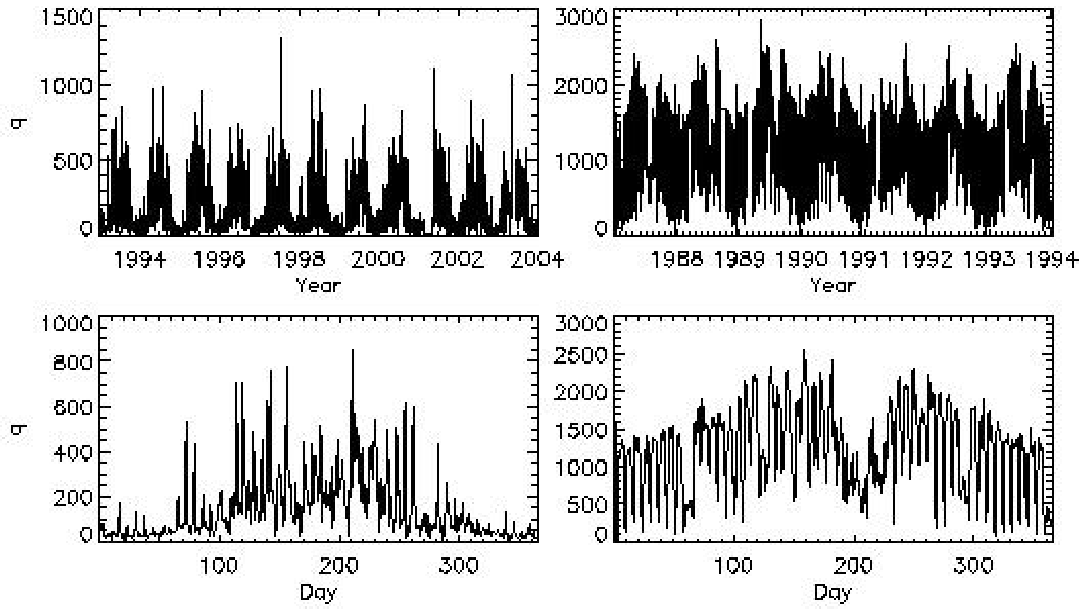


**FIGURE 2 Flow time-series for cycle paths 0725 (left, recreational) and 5501 (right, utilitarian) for the whole measurement period (top panel) and for 1993 (bottom panel).**

**3. THE BI-LEVEL WEATHER MODEL**

We developed a bi-level 'weather' model, described by the two following equations:

$$\ln q_{est} = \ln c + \ln q_0 + b * WP \quad (1)$$

$$WP = f(W_1,...,W_m) \quad (2)$$

Equation 1 is the upper level of the bi-level model. In this equation, $q_{est}$ is the estimated or modelled daily flow, $c$ is a seasonal factor, $q_0$ is the flow for a day with 'average' weather (when $WP = 0$) and $WP$ is a weather parameter that 'describes' the weather. The upper level is thus a linear relation between the ln (natural logarithm) of the daily flow and the weather parameter. The rate, in which demand depends on weather, is given by slope $b$. The upper level is discussed in section 3.1.

Equation 2 is the lower level in which the weather parameter $WP$ is estimated. $WP$ is a function of weather observables ($W_1$, …, $W_m$), which are temperature, visibility, humidity, rate of precipitation, the rate of cloud cover and wind force. The lower level is discussed in section 3.2.

In the following sections we will compare $q_{est}$ with the observed flows $q_{obs}$. We adopt the root-mean-square (rms) of the residuals as a measure for the quality of the model. The residuals are estimated for each day and each cycle path, and they are defined as the differences: $\Delta\ln q = \ln q_{obs} - \ln q_{est}$. A low rms indicates that the model fits the observations quite well.

**3.1. Upper level**

In the upper level, the demand is related to the weather. We use the logarithm in equation 1, because we assume that an absolute improvement in weather will uniformly lead to a relative increase in demand. The rate of relative increase can however be different for utilitarian and recreational paths. This rate, described by parameter $b$ in equation 1, is expected to be high for recreational paths, because the choice to make a trip for pleasure depends strongly on weather. The influence of weather will be less severe for utilitarian paths. In the extreme case, parameter $b$ might be close to 0, if the path is mainly used by captives (e.g. school children).

As explained in the introduction, policy makers can use the weather model to compare 'standardized' flows $q_0$ from different locations and during different years. Our sample of locations is too limited for an extensive spatial analysis. However, in section 4.3. we look for temporal trends in demand, by comparing $q_{obs}$ with $q_{est}$ over several years.

The seasonal factor $c$ in equation 1 corrects, among other things, for the fact that there is extra demand (for recreational paths) or less demand (for utilitarian paths) during the school holidays. It will however also complicate the calibration of the model. In 'calibrating' our weather model, we therefore excluded the school holidays and we assumed that $c = 1$ for all other weeks. In section 4.2 we study the remaining seasonal demand fluctuations.

Thus, for each day of the week and each cycle path we need to estimate $q_0$ and $b$ (given that $c = 1$) from a set of observed daily flows and corresponding values of $WP$. This was done by adopting a least square fit. The results are given in section 4.1.

### 3.2. Lower level

The weather parameter *WP* describes how cyclists value the weather. A high value corresponds with weather conditions that favor cycling. According to the upper level, the relative demand increases proportional with *WP*. By keeping the upper level simple, we shifted the possibly complicated relation between weather and demand to the lower level.

We studied this relation in the following way. First, we selected weather observables that are (most) strongly correlated with ln $q_{obs}$. These observables are temperature, the amount of sunshine, precipitation and wind force. We have examined other parameters, like humidity and visibility , but none of them will lead to improvements in the model. We thus decided to select the following four observables: the mean temperature over 24 hours *TG* (in degrees Celsius), the duration of sunshine *SQ* (in hours), the duration of precipitation *DR* (in hours) and the mean wind force over 24 hours *FG* (in m/s). The symbols used were taken from the KNMI abbreviations. We used the mean (rather than maximum) temperature, because many cyclists make their trips in the morning, during which the temperature lies closer to the mean. Similarly, we used the duration instead of the amount of precipitation. Cyclists are put off by a long period of moderate rainfall, but one short heavy thunderstorm will only have a temporary effect.

The second step is to determine the relation between the selected weather observables and *WP*. A straightforward relation would be a linear relation:

$$WP = a_{zp} + a_{TG}TG + a_{SQ}SQ + a_{DR}DR + a_{FG}FG \quad (3)$$

The coefficients $a_{TG}$, $a_{SQ}$, $a_{DR}$ and $a_{FG}$ determine how much the individual observables contribute to *WP*. The value of $a_{zp}$ is chosen such that the 'average' weather is at $WP = 0$. If we combine equations 1 and 3 (upper and lower level), ln $q_{est}$ is just a linear combination of four observables. If *b* is a free (but positive) parameter, then we may fix one of the weather coefficients. We chose $a_{TG} = 1$. Note that $a_{TG}$ must be positive, if we require that *b* is positive (because temperature and demand are positively correlated). We then applied a multiple linear regression fit for each cycle path and day of the week, and obtained the following average values: $a_{SQ} = 0.7$, $a_{DR} = -0.7$ and $a_{FG} = -1.0$. As expected, high temperatures and sunshine have a positive effect on demand, whereas precipitation and wind have a negative effect.

However, a linear model is not the best model to describe demand fluctuations. We conclude this from an inspection of the (mean) residuals. For each of the four observables, we defined (small) ranges in which we aggregated observations. For each aggregate we determined the average value of the residuals, i.e. the mean of $\Delta\ln q$. The results for the linear model are shown in the upper panel of Figure 3. From left to right, we show the mean residuals for *TG*, *SQ*, *DR* and *FG* respectively. We discriminated between utilitarian (open boxes), mixed (crosses) and recreational (asterices) cycle paths. The center and bottom panel will be discussed later.

From the Figure we conclude that the residuals show systematic deviations from 0. The flows are lower than expected (negative residuals) for $TG > 18$ degrees Celsius. This can be explained by the fact that it is less attractive to cycle when temperatures become very high. For *SQ*, the residuals are too high for low, and too low for high values. The opposite trend is visible for *DR*, which also has an opposite effect on bicycle demand. For both *SQ* and *DR*, the contribution to *WP* is therefore too low for short, and too high for long periods of sunshine or precipitation. This non-linearity is rather logical. The difference between zero and one hour of sunshine or precipitation has a larger effect on how people value the weather than a difference between for example 10 and 11 hours. For the wind force, the opposite is the case. Like *DR*, it has got a negative effect on demand. However, for large *FG*, the residuals are too low. The demand is thus lower than expected, which suggests that the (negative) contribution to *WP* is under estimated. The explanation is that a small breeze can be felt as quite pleasant, but strong winds have a disproportional negative effect on demand.

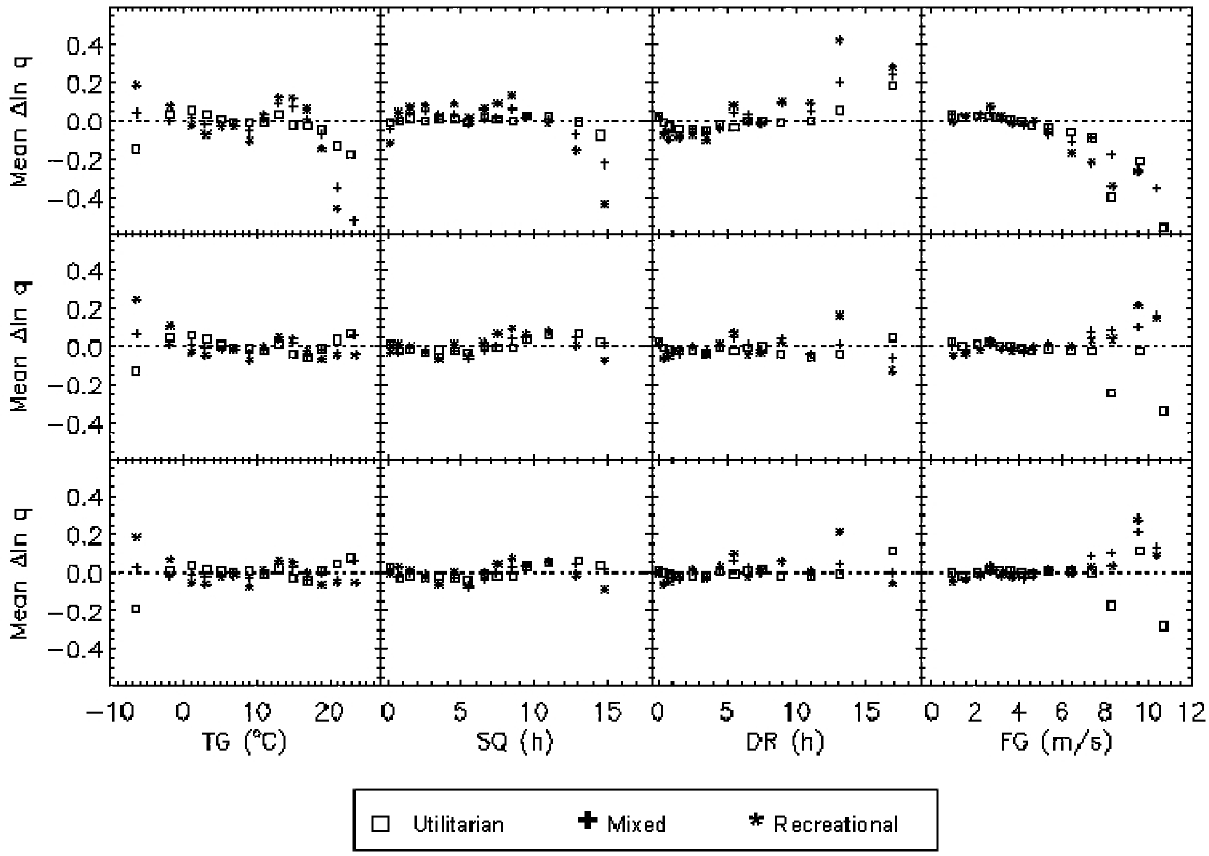


**Figure 3: Mean residuals for utilitarian, mixed and recreational cycle paths as function of weather observables (temperature TG, sunshine SQ, precipitation DR and wind force (FG). For the linear (upper panel) and non-linear models (lower panels).**

We therefore adapted our model by defining the following parameters:

$$W_{Temp} = TG \qquad \text{for TG} \leq 18 \text{ degrees Celsius} \tag{4a}$$
$$W_{Temp} = TG - 0.3(TG - 18) \qquad \text{for TG} > 18 \text{ degrees Celsius} \tag{4b}$$

$$W_{Fair} = SQ^{1/2} - 0.7DR^{1/2} \tag{5}$$

$$W_{Wind} = FG^{3/2} \tag{6}$$

These parameters include the non-linear effects, described above. In equation 5, *SQ* and *DR* are combined, because sunshine and precipitation are obviously negatively correlated. Fair stands for good (lots of sunshine) or bad (lots of rain) weather. The parameters $W_{Temp}$, $W_{Fair}$ and $W_{Wind}$ are uncorrelated or only weakly correlated (correlation coefficient ~ 0.2 in case of correlation between $W_{Temp}$ and $W_{Fair}$).

The ranges of the three parameters are quite different, which makes it difficult to illustrate their contribution to *WP*. We solved this problem by normalizing each parameter. This was done as follows. We gathered all weather data from 1985 to 2005, and for each parameter we estimated the average and standard deviation over that period. From each measurement we then subtracted the average and divided the result by the standard deviation. Each normalized parameter thus has an average equal to 0 and a standard deviation equal to 1. The average *WP* is also 0 and the different parameters that contribute to *WP* all have the same (dynamical) range. For our adapted model, equation 3 now becomes:

$$WP = a_{Temp}W_{Temp} + a_{Fair}W_{Fair} + a_{Wind}W_{Wind} \tag{7}$$

We applied a multiple linear regression fit for each cycle path and day of the week, and when we required that $a_{Temp}^2 + a_{Fair}^2 + a_{Wind}^2 = 1$ (variance in $WP \approx 1$), we obtained the following average values: $a_{Temp} = 0.8$, $a_{Fair} = 0.5$ and $a_{Wind} = -0.3$. Temperature is thus the parameter that contributes the most to *WP*. It is possible that the effects of rain are slightly under estimated, because we used 24h instead of day-time figures. The wind force contributes the least, but it still has a significant, negative, effect on *WP*.

The mean residuals for this model are shown in the center panel of Figure 3. From this panel we conclude that most significant deviations, shown in the upper panel, have disappeared. Only for very low temperatures and high wind forces there still are some significant deviations, but these deviations are different for utilitarian and recreational paths. We conclude that we can adopt this model as the best fit we have so far.

If we do not use average values, but adopt $a_{Temp}$, $a_{Fair}$ and $a_{Wind}$ for each cycle path and day of the week, we get mean residuals that are shown in the lower panel of Figure 3. Note that the differences between the center and lower panel are marginal.

## 4. RESULTS

In this section we show the results of our weather model. In section 4.1 we discuss the results from the multiple linear regression fit, described in the previous section. In section 4.2 we estimate the seasonal coefficient $c$ (equation 1). This estimate is included in the final estimate of $q_{est}$. In section 4.3 we determine the annual average of $q_{obs}$ and $q_{est}$. By comparing these two, we are able to analyze trends over the years.

### 4.1. The model coefficients

We estimated the weather coefficients $a_{Temp}$, $a_{Fair}$ and $a_{Wind}$ for each cycle path and each day of the week, as described in section 3.2. The main conclusion is that the coefficients are quite similar for the different cycle paths and days. There are however some small, but statistically significant differences, which can be summarized as follows. The coefficient $a_{Temp}$ is slightly higher (0.8 versus 0.7) for utilitarian traffic than for recreational traffic. This difference is compensated by the fact that $a_{Fair}$ is somewhat higher for recreational traffic. From this we conclude that recreational traffic is more sensitive to $W_{Fair}$, which is mainly season independent. Because recreational trips are non regular trips, it is expected that the current weather situation will have a relatively strong influence on the trip choice. We also observed that the negative influence of wind force appears to be more important for cycling paths in Gouda than in Ede ($a_{Wind}$ about -0.30 in Ede versus about -0.35 in Gouda). The difference may be explained by the fact that Ede lies in the Dutch national forest (Veluwe), in which the wind is subsided.

The coefficients $q_0$ and $b$ (equation 1) are much more variable. In Figure 4 we illustrate the results for a recreational path (ID 0725) in Ede (upper panel) and an utilitarian path (ID 5501) in Gouda (lower panel) for Thursdays (left) and Sundays (right). The Figure shows significant differences in the slope $b$. The slope is very shallow for the utilitarian path on a Thursday (bottom left). The slope becomes steeper for recreational paths and for Sundays. The results in Figure 4 are illustrative for all cycle paths. For all utilitarian paths, the slopes $b$ all lie between 0.16 and 0.26 for working days, and are on average 0.4 for Saturdays, and almost 0.6 for Sundays. For recreational paths in Gouda, $b$ is about 0.5 for working days, 0.6 for Saturdays, and 0.7 for Sundays. The steepest slopes are found for recreational paths in Ede: between 0.8 and 1.2 for all days. The slopes of mixed paths lie in between. Note that we found very similar slopes for different working days, i.e. observed differences were not significant.

We interpret these results as follows. Less obligatory trips (recreational trips) are much more influenced by weather than utilitarian trips. In this respect, there is also quite a large difference between the recreational cycle paths in Ede and Gouda. On the recreational paths in Ede, cyclists appear to be the most sensitive to weather. An explanation may be that the recreational paths in Ede mainly attract tourists. These people, contrary to for example people who use the bicycle for a sports or shopping motive, probably make the least obligatory trips of all. Their trips have no other purpose, but to enjoy the environment and the good weather.

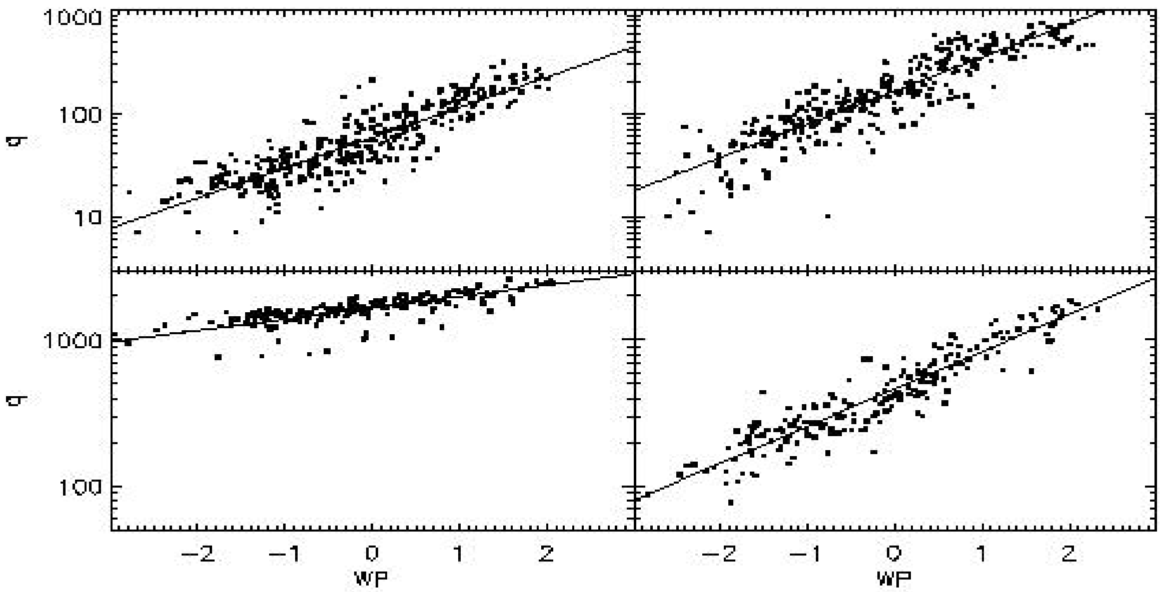


**Figure 4 Relation between weather and cycle demand for an utilitarian path (upper panel) and an recreational path (bottom panel) on Thursdays (left) and Sundays (right)**

The standardized demand $q_0$ depends on the strength of local OD flows, and is less relevant for this study. However, for policy makers it may be important to know how demand changes during the week. We therefore estimated the ratio's between the daily demands and the weekly averages. Again, we find marginal differences between working days. These working days show about 20% more traffic than average for utilitarian paths. The flows are much smaller on Saturdays and Sundays: on Saturdays 60%, and on Sundays only 45% of the average. The opposite is true for recreational paths. Flows are smaller during working days, about 70% of the average. On Saturdays flows are 20% larger than average, and on Sundays the flow is more than 2 times the average flow.

These results are obvious. Utilitarian paths mainly serve commuting trips, school trips and shopping trips, which are dominant on working days, while recreational trips are dominant in the weekends.

### 4.2. Seasonal effects

The coefficient *c* in equation 1 describes the seasonal variations. We estimated ln *c* from the weekly residuals. Per week (from week 1 to week 53), we determined the average weekly residual for working days, Saturdays and Sundays. In Figure 5 we show the residuals for working days as an example. This was done for utilitarian cycle paths (upper panel), mixed paths (center panel) and recreational paths (lower panel). The results are shown for paths in Ede (crosses; asterices during the school holidays)) and Gouda (open boxes; filled boxes during the school holidays).

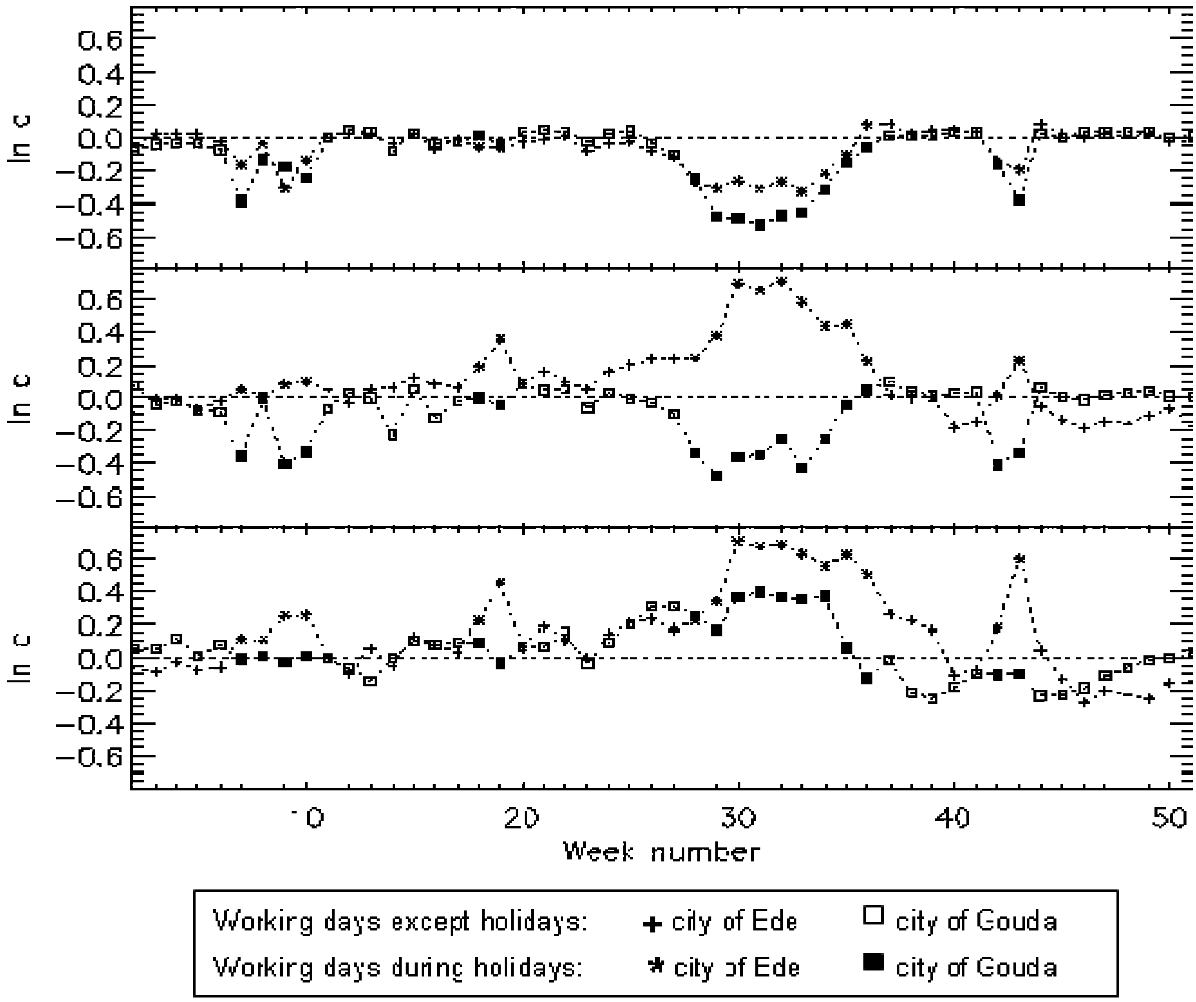


**Figure 5 Weekly variations in Ede and Gouda for utilitarian paths (upper panel), mixed paths (center panel) and recreational paths (lower panel).**

Figure 5 shows that the variations are rather similar for utilitarian paths in Gouda and Ede (upper panel). Moreover, outside the school holiday period, seasonal variations are very small (ln $c$ ~ 0), while the demand drops significantly during the school holidays. For recreational paths (bottom panel), seasonal variations are quite variable and also different for paths in Gouda and Ede. For both locations, though, a weak trend is detectable. Volumes are higher than expected during the spring, and lower than expected during the autumn. During the school holidays, demand is significantly higher than normal. The mixed paths (center panel) show different results for Gouda and Ede. In Gouda demand is relatively lower during the school holidays, which would suggest that these paths mainly serve utilitarian traffic. In Ede the opposite is the case, which suggests that these paths mainly serve recreational traffic. Because these paths combine the properties of recreational and utilitarian paths, but not always in the same proportion, we decided to exclude them from further analysis. We also excluded the school holidays, because the demand is quite different from the non-holiday demand, and also not the same for different locations.

We estimated *c* for Saturdays and Sundays as well. Both days show rather similar trends, in which demand is larger than expected in the spring, but lower than expected during (the end of) autumn. We used the estimates of *c* to improve the model flows $q_{est}$.

**4.3. Annual variations**

One of the objectives of policy makers is to monitor cycle flows. It is however difficult to disentangle long term trends from 'accidental', weather related, fluctuations. With our weather model we have estimated expected flows. We can compare their annual averages with those of the observed flows in order to recover long term trends. In Figure 6 we show the ratio between the annual average for each year ($q_{year}$) and the observed annual average of 1993 ($q_{1993}$). The latter is used to normalize all ratio's to the same base. We show the ratio's for the observed (symbols) and estimated averages (dotted lines). This was done for the aggregates of utilitarian (upper panel) and recreational (bottom panel) paths in Gouda (crosses) and Ede (open boxes).

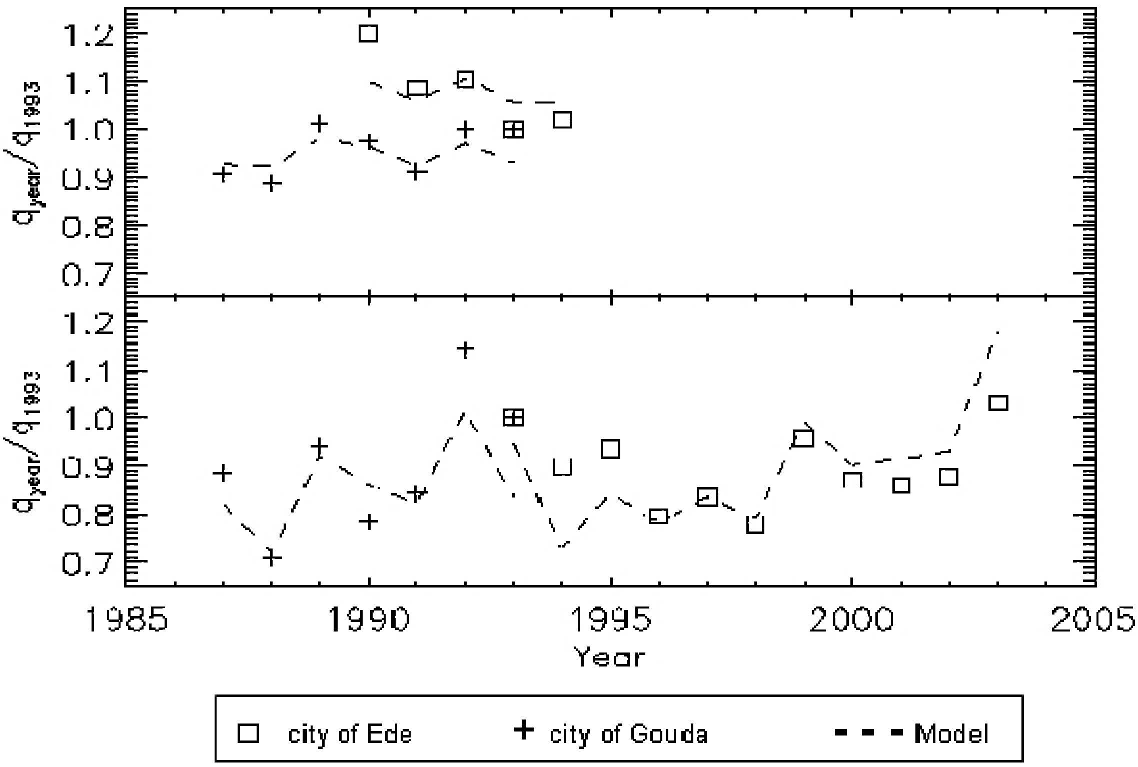


**Figure 6 Ratio between annual averages and the observed annual average of 1993 for utilitarian (upper panel) and recreational (bottom panel) paths in Ede and Gouda.**

Figure 6 shows that the model follows the 'accidental' fluctuations in the observations quite well. Trends are revealed from the deviations between observed and estimated annual flow ratio's. The long year trends are not unambiguous. For the paths in Gouda, no trend appears to be present. If any, the trend seems to be upwards, although this trend is too weak and the period too small to draw any conclusions. For the paths in Ede, there appears to be a stronger trend. Both for the utilitarian and recreational paths, the trend is downwards. If we would only consider the observed flows, this trend is less clear, as this downward trend is offset by better weather conditions during the last few years (from 2000 onwards).

We illustrate that it is possible to detect long term trends in cycling patterns. However, studies of long term trends are only useful when a large number of cycle paths in different areas are analyzed. In that case, meaningful comparisons can be made.

## 5. RELIABILITY OF THE MODEL

In the previous section, we showed that the weather model is suitable for estimating cycle flows in the Netherlands. However, the remaining variation is large. About 30 – 50% of the total demand variation is left in the residuals. At first sight, it is not clear what causes this variation. There are no significant systematic errors in the weather model. We concluded that the inclusion of other weather parameters will not lead to better demand estimates, and seasonal variations are included and only have a marginal effect on the model results. The variation due to the random arrival process of cyclists (described by a Poisson distribution) is also much smaller, and therefore negligible.

Some of the variation may be caused by inaccuracies in the weather measurements. As mentioned before, we used 24 hours aggregates, which are also not very local. Although these figures are not most accurate, we suggest that it only explains a part of the remaining variation. Another possibility is that the variation in the residuals is caused by local fluctuations in demand, which are not weather related. In that case, the fluctuations of two different locations should be uncorrelated. In other words, the residuals from different cycle paths should be uncorrelated.

We performed three correlation analyses: between paths of the same type and located in the same town, between paths of the same type, but located in different towns, and between utilitarian and recreational paths, located in the same town. For some of these correlations, there was an overlap of many years in the time-series. For other comparisons, relatively few data were available. Fortunately, we always have residuals for the year 1993.

We find a significant positive correlation between the residuals when they are from paths of the same type, irrespective of their location. The correlation coefficients are 0.5 and 0.3 respectively for utilitarian and recreational paths during working days, and they are 0.6 and 0.5 respectively during weekends. There is not only a spatial correlation between residuals, but also a temporal correlation. Despite the fact that we have corrected for seasonal variations, we find a significant correlation between the residuals of successive days. The correlation coefficients are 0.4 for utilitarian and 0.3 for recreational paths.

These correlations suggest that a non-local component with time-scales longer than a day is missing in the model. However, although these correlations may be significant, they are not very strong. If we could somehow include this non-local component in the model, we would decrease the variation in the residuals with 30% and 20% respectively for utilitarian and recreational paths during working days, and with 40% and 30% respectively during weekends. Thus, on average 70% of the variation in the residuals is locally constrained. Moreover, we find no correlation between the residuals from recreational and utilitarian paths. If there is some non-local component missing in the model, this component is different for utilitarian and recreational traffic.

We conclude that most of the variation in the residuals is caused by local fluctuations in demand, which may not be predicted by a generic model. The remaining variation is not locally constrained. Non-local demand fluctuations may be included in a generic model, but more research is needed to find the causes for these fluctuations.

## 6. CONCLUSIONS

For 16 cycle paths in the Dutch cities of Ede and Gouda, we analyzed time-series of 24 hours cycle flows in the period 1987-2003. About 50 to 70% of the variations in these flow time-series can be explained by the 'weather model' that was described in this paper.

The weather model is a bi-level model. The upper level is a linear relation between demand and the weather parameter. In the lower level, the weather parameter is estimated. The weather parameter describes how cyclists value the weather. The weather parameter depends on the following observable parameters (in order of importance): average 24h temperature, the amount of sunshine, the duration of precipitation, and the average wind force. Different user groups (utilitarian and recreational) appear to value the weather in more or less the same way. The influence of weather (the weather parameter) on demand is however very different for different user groups. Recreational cyclists are much more sensitive to weather than utilitarian traffic.

With the weather model it becomes possible to disentangle long term trends from accidental, weather related, variations. We found no evidence for a long term trend for the paths in Gouda, but for cycle paths in Ede, there is some evidence that the observed demand lagged the expectations in the second half of the time-series. This apparent decrease in demand was off-set by better average weather conditions around the change of the millennium. However, studies of long term trends only become useful when more locations are included.

Residuals were examined to upgrade the weather model. From this we concluded that the best model is not linear. However, many of the fluctuations can still not be described by the non-linear model. There are some seasonal variations, but these are relatively small for recreational paths, and negligible for utilitarian paths.

From a correlation analysis between residuals of different cycle paths, we concluded that most (about 70%) of the remaining fluctuations in the residuals is probably locally constrained, and cannot be described by a generic model. However, we used 24h weather measurements in this study, which may have led to inaccuracies in our model. Local variations in weather that take place within the morning rush hour, for example, may have a large effect on bicycle demand fluctuations during the rest of the day.

About 30% of the remaining variation is not locally driven. We suggest that this variation may partly be explained by weather variations within 24h that are similar for different locations in the Netherlands, but that some of this variation is not weather-related. More detailed weather measurements and a study of other 'attributes' are needed to find the causes for this variation. Such a study could consist of a survey in which cyclists are asked about their trip making behavior. More knowledge of this behaviour would allow for better predictions of any given path for which the mix of users is known.

This paper focuses on developing a weather model. The model and the results are not yet applicable to practioners and policy makers. However, one of our first findings is already relevant for policy makers: so far, there is no evidence for a positive long term trend in volumes of bicycle traffic, despite considerable policy interventions to promote cycling.

In a next phase of the research we will expand on additional hypotheses, enabling to 'standardize' flows from different locations and also from different years with the help of 'weather corrections'. The standardization of flows is very relevant to practitioners and policy makers in the context of evaluating cycle policy interventions on a local and regional scale.

After the application on bicycle networks we want to investigate the hypothesis that the model is useful to describe fluctuations in day-to-day traffic of motorized flows to national parks and specific destinations for outdoor recreation. An ecologically and economically sustainable management of such areas requires insight in the number of visitors. In that context a distinction between systematic and random variation of visitor flows is important *(13).*

**REFERENCES**

(*1*) Baltes, M. Factors Influencing Nondiscretionary Work Trips by Bicycle Determined from 1990 US Metropolitan Statistical Area Data. In *Transportation research record: Journal of the Transportation Research Board, No. 1538.* Transportation Research Board of the National Academies, Washington, D.C., 1996, pp. 96-101.

(*2*) Dill, J., and T. Carr. Bicycle commuting and facilities in major US cities. In *Transportation research record: Journal of the Transportation Research Board, No. 1828.* Transportation Research Board of the National Academies, Washington, D.C., 2003, pp. 116-123.

(*3*) Waldman, J.A. *Cycling in Towns: A Quantitative Investigation*. LTR1 Working paper 3. Department for Transport, London, 1977.

(*4*) Parkint, J., Wardman, M., and M. Page. Estimation of the determinants of bicycle mode share for the journey to work using census data. *Transportation*, Vol. 35, No. 1, 2008, pp. 93-109.

(*5*) Rietveld, P., and V. Daniel. Determinants of bicycle use: do municipal policies matter? *Transportation Research A*, Vol. 38, 2004, pp. 531-550.

(*6*) Hanson, S., and P. Hanson. Evaluating the impact of weather on bicycle use. In *Transportation research record: Journal of the Transportation Research Board, No. 629.* Transportation Research Board of the National Academies, Washington, D.C., 1977, pp. 43-48.

(7) Emmerson, P., Ryley, T.J., and D.G. Davies. The impact of weather on cycle flows. *Traffic Engineering and Control*, Vol. 39, No. 4, 1998, pp. 238-243.

(*8*) Nankervis, M. The effect of weather and climate on bicycle commuting. *Transportation Research Part A*, Vol. 33, No. 6, 1999, pp. 417-431.

(*9*) Nagendra, S.S.M, and M. Khare. Principal component analysis of urban traffic characteristics and meteorological data. *Transportation Research D*, Vol. 8, 2003, pp. 285-297.

(*10*) Jaarsma, C.F. Temporal variations of bicycle traffic flows in the Netherlands. In *Proceedings of the eleventh international symposium on transportation and traffic theory*, Yokohama, Japan, 1990, pp. 443-459.

(*11*) Jaarsma, C.F., and F.J. Wijnstra. Coincidence or trend? A method for analysis of temporal variation of daily bicycle traffic flows. In *Proceedings of the seventh world congress on transportation research*. CD-ROM, Sydney, Australia, 1995.

(*12*) Koninklijk Nederlands Meteorologisch Instituut (KNMI). *Daggegevens KNMI-stations*. http://www.knmi.nl/klimatologie/daggegevens/download.cgi, Accessed 2006.

*(13)* Loomis, J.B. Counting on Recreation Use Data: A Call for Long-Term Monitoring. *Journal of Leisure Research,* Vol. 32, 2000, pp. 93-96.